Mapping Within-field Variability Using Airborne Imaging Systems: A Case Study from Missouri Precision Agriculture

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Abstract: This study investigated the use of airborne image data to provide estimates of within-field variability in soil properties and crop growth as an alternative to extensive field data collection. Hyperspectral and multispectral images were acquired in 2000, 2001, and 2002 for central Missouri experimental fields. Data were converted to reflectance using chemically-treated reference tarps with known reflectance levels. Geometric distortion of the hyperspectral pushbroom sensor images was corrected with a rubber sheeting transformation. Statistical analyses were used to relate image data to field-measured soil properties and crop characteristics. Results showed that this approach has potential; however, it is important to address a number of implementation issues to insure quality data and accurate interpretations.
Keywords: Airborne, Hyperspectral, Precision agriculture, Soil, LAI, Yield

1. Introduction

Precision agriculture, also known as site-specific crop management, is an information-based management-intensive approach to farming. Instead of managing a field as a whole, the philosophy of precision agriculture is to manage individual areas within a field, taking into account spatial variability in soil, landscape, and other factors affecting crop production. By accounting for within-field variability and applying inputs such as fertilizers and pesticides accordingly, precision agriculture has the potential to provide maximum return and reduce environmental loadings from agricultural chemicals.

Widespread implementation of precision agriculture will require methods that efficiently and economically characterize variations in soil properties, crop growth, and other factors affecting crop yields. An efficient way to detect spatial differences in crop and soil conditions within a field is through image-based remote sensing (RS) [1]. A variety of aircraft- and satellite-based RS data sources, such as photographs, videographs, and multispectral and hyperspectral images, have become available for use in agricultural applications. Application of these remote sensing images is complicated because image acquisition requires cloud-free sky conditions, the signal is attenuated by the atmosphere, and image interpretation is a complex function of the sun/ sensor/ target geometry [2].

The objective of this study was to investigate the ability of airborne hyperspectral- and multispectral-image data to estimate within-field variability in soil properties and crop growth.

2. Data Collection, Processing, and Analysis

1) Study Site and Ground Data Collection

Data were collected on two research fields (Field 1, 35 ha and Field 2, 13 ha), managed in a corn-soybean rotation and located near Centralia, Missouri, USA (-92.12 E, 39.97 N). Soils are claypan soils of the Mexico series (fine, smectitic, mesic aeric Vertic Epiaqualfs) and the Adco series (fine, smectitic, mesic aeric Vertic Albaqualfs). Surface textures range from a silt loam to a silty clay loam. The subsoil "claypan" horizon(s) are silty clay loam, silty clay or clay, and commonly contain as much as 50 to 60% smectitic clay.

Ground measurements used in the soil property analysis included soil chemical properties, texture, and apparent electrical conductivity (EC_a). The field was soil-sampled on a 30-m grid to a 15-cm depth in the spring of 2001. Samples were analyzed for P (Bray 1 extractable), K, Ca, Mg (ammonium acetate extractable), cation exchange capacity (CEC; sum of bases), organic matter (OM; wet oxidation), and pH (salt), using standard University of Missouri procedures [3]. Soil EC_a, which has been shown to be strongly related to soil texture on these fields [4], was measured in the fall of 1999 using two commercial sensor systems, the Geonics EM38* and the Veris 3100.

Seven monitoring sites in Field 1 and five in Field 2 were selected to represent the range of variability present in the fields for LAI and crop yield. Destructive crop sampling for LAI was carried out within a 1-m long row section for corn and soybean. Leaf area was measured with a LI-COR leaf area meter (LI-3100), in which the projected image of a leaf sample traveling under a fluorescent light source is reflected by a system of mirrors to a solid-state scanning camera. Non-destructive LAI measurement was performed with a plant canopy analyzer (PCA, LAI-2000, LI-COR Inc.), which estimated LAI from light measurements above and below the canopies at five solid angles using a hemispherical cosine-corrected sensor. Crop yield was obtained both by hand harvesting and with a yield monitor-equipped combine.

* Mention of trade names or commercial products is solely for the purpose of providing specific information and does not imply recommendation or endorsement by USDA or RDA.

2) Bare Soil Image Processing and Analysis

Airborne images were taken under bare soil conditions prior to crop planting and/or emergence in the spring of 2000, 2001, 2002. The aerial hyperspectral (HS) imaging system used in this study was the Real Time Digital Airborne Camera System H3 (RDACSH3) pushbroom prism-grating scanner operated by Spectral Visions Midwest [5]. RDACSH3 images included 120 bands ranging from 471-828 nm on a 3-nm interval. As operated, the system provided a spatial resolution of 1 m and a spectral resolution of 1.5 nm full width at half maximum (FWHM).

Significant geometric distortion was observed in the HS images, probably due to variations in velocity and attitude of the aircraft caused by air turbulence. Compensation for this distortion was implemented in several ways. The image provider used a gyro-stabilized camera mount with an error of +/-5 degrees. Distortions caused by the roll of the aircraft were pre-processed by finding a feature that should be straight, like a road in the direction of flight, and drawing a line to delineate that feature in the raw image. Software was then used to shift image pixels left or right to make the feature straight. After this systematic correction from the vendor, the images still needed to be geo-referenced for comparing with measured ground data. To do this, we applied a rubber sheeting model using piecewise polynomials for image rectification.

Data from the airborne imaging spectrometer was expressed as a solar irradiance curve in uncalibrated digital numbers (DN). We used empirical line correction methods to obtain an apparent reflectance factor (ρ_a) using chemically-treated reference tarps to minimize effects of sensor and solar variation. This approach has the advantages of full compensation for atmospheric effects and no need for ground operations other than pre-flight tarp deployment. Details of this procedure have been reported elsewhere [1].

To compare the usefulness of the HS data to multispectral data, we averaged reflectance values of the HS data spectrally to make Landsat-like bands (LLBs). Another data reduction method, principal component analysis (PCA), was also applied to the 120 HS data layers. The first five principal components (PCs) of each image were used for data analysis because these five PCs represented 98 % or more of the variance in the image data. In addition, only these first five PCs showed a spatial structure similar to known field patterns providing an indication that additional PCs consisted primarily of measurement noise. Three data sets, the first consisting of the 120 HS data layers, the second consisting of 4 Landsat-like data layers, and the third consisting of 5 PC data layers, were used for analysis.

A variety of statistical analyses, from simple to more complex, were used to examine the relationship of the HS and Landsat-like reflectance data to soil texture, chemical properties, and EC_a. First, Pearson correlation coefficients (r) were calculated for each combination of reflectance and soil variables. Second, stepwise multiple linear regression (SMLR) analysis was used to identify a set of statistically significant wavelengths that could be used to explain soil properties as a function of HS reflectance for each of the three years. Third, multiple regression (MR) models were used to estimate soil properties from the 4 LLBs and from the 5 PCs.

3) Crop Image Processing and Analysis

Airborne HS and satellite multispectral (MS) images were obtained several times for Fields 1 and 2 during the 2001 and 2002 cropping seasons. HS data were obtained using the RDACSH3 system described above and the Airborne Imaging Spectroradiometer for Applications (AISA) [6] system operated by CALMIT (Center for Advanced Land Management Information Technologies), University of Nebraska, USA. Spectral coverage of the AISA sensor was from 450 nm to 900 nm, while the spatial resolution (1.5~4 m) and number of spectral bands (25~70) were selectable according to the requirements of the particular study. For this research, the AISA system was configured to provide 24 bands ranging from 467 nm to 891 nm and a 1.5-m spatial resolution. Geometric and radiometric corrections for the airborne sensor data used the same procedures reported above for bare soil images.

Multispectral satellite images used in this study were obtained from the IKONOS and Quickbird satellites and had a 4-m spatial resolution. As provided by the vendor, the satellite images were georectified and had been radiometrically corrected to adjust brightness and contrast to compensate for sensor sensitivity changes. No further geometric or radiometric calibration was done after we received the images.

Normalized Difference Vegetation Index (NDVI; (NIR-RED)/(NIR+RED)) was calculated from the images at points coincident with the hand-harvested areas. Images used for LAI estimation were obtained with the multiple sensors described above, resulting in data with different levels of radiometric calibration and spatial resolution, as well as, and different amounts of atmosphere between the sensor and the ground. Correlation and regression analyses were used to investigate the relationships of LAI and yield to NDVI.

3. Results

1) Soil Properties

In general, soil chemical properties were negatively correlated with reflectance (Fig. 1) over the RDACSH3 measurement range (471 to 828 nm). Blue wavelengths were most strongly related to ground-measured soil properties, including chemical properties (Fig. 1), clay content, and soil EC_a. PC 4 and PC 1 from the 2000 and 2002 bare soil images (dry soils) were highly correlated to soil chemical properties and EC_a, respectively. Bare soil images obtained in dry conditions (2000 and 2002) were better for estimating soil chemical properties and EC_a. The moist soil (2001) image was better for estimating soil texture.

SMLR models using HS data exhibited higher R^2 values than MR models using LLBs demonstrating the value of HS images. However, results with Landsat-like images were still quite good, and may be more acceptable for practical application, considering data volume, efficiency and overfitting concerns. Both data reduction approaches - creating LLBs and application of PCA - reduced the volume of data while maintaining the ability to develop relationships with soil properties. Soil EC_a, particularly the shallow measurement from the Veris 3100, provided a dense dataset related to soil texture that could then be related to HS data, providing a two-stage calibration of texture to bare soil images.

2) LAI and Yield

NDVI showed a strong variation over the growing season, as did LAI. Curvilinear relationships between NDVI and leaf area index (Fig. 2) were found for data obtained throughout the growing season at monitoring sites within a corn field (Field 2, 2002). The large increase in NDVI between DOY 176 and 179 (Fig. 2) might be due to either calibration differences between the different sensors used or rapid growth of the corn (corn was at the V18 growth stage, one week away from the reproductive phase). NDVI measured at crop development stage R4 was better for estimating LAI than was NDVI at R6. However, NDVI at R6 was better for estimating soybean yield than NDVI at R4 (Table 1).

5. Conclusions

Soil reflectance is affected by a number of interrelated soil properties. Soil color as related to chemical composition (e.g., organic matter and oxides), moisture, and texture are widely recognized as important soil properties that change the spectral reflectance of the surface soil. In this study and related work [1], we have found all of these soil parameters to be related to data obtained from airborne HS images.

NDVI, an image-derived vegetation index, was compared with measured LAI and yield data for both corn and soybean. Over the growing season, the general trend in NDVI was similar to that in LAI. NDVI measured at development stages R4 and R6 could be used to estimate LAI and yield in soybean.

In general, statistical models using HS data exhibited higher R^2 values than those using MS data. However, results with MS data were still quite good, and may be more acceptable for practical application, considering costs, data volume and processing efficiency, and potential overfitting concerns associated with HS images.

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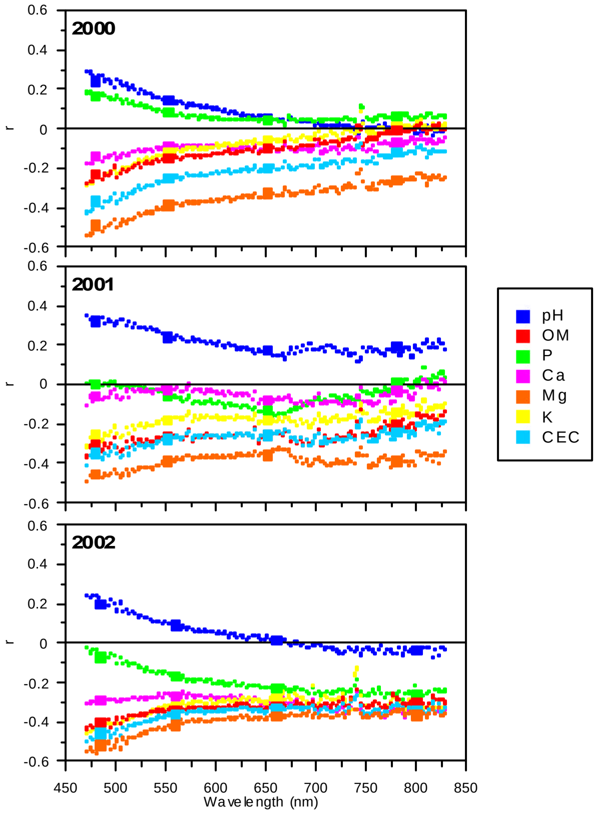

Figure 1. Correlations of 120 hyperspectal wavelengths and four Landsat-like bands (LLBs, larger symbols) to chemical properties.

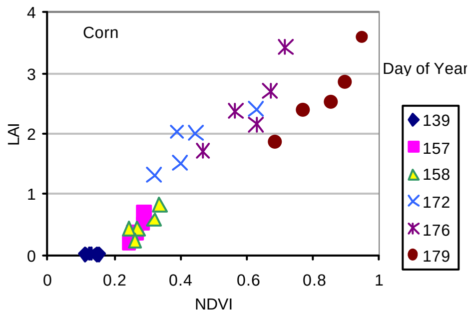

Figure 2. Relationship between LAI and NDVI for corn over several dates in 2002

Table 1. Estimation of LAI and yield from NDVI at different soybean development stages.

Development stage		Slope	Intercept	R^2
R4 (full pod)	LAI	7.19	-2.10	0.68
	Yield	2289.9	454.8	0.48
R6 (full seed)	LAI	14.31	-5.57	0.54
	Yield	5599.1	-1565.5	0.69